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Utilizing the Error Correction Model to Investigate the Impact of Fluctuations in Bank Deposits on the Money Supply

Mayson A. Hussein	Munaf Y. Hmood
maysoon.Abdulhusseinl1201a@coadec.uobaghdad.edu.iq	munaf.yousif@coadec.uobaghdad.edu.iq
Department of Statistic, College of Administration and Economics, University of Baghdad, Baghdad, Iraq.	

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Correspondence:
Munaf Y. Hmood
munaf.yousif@coadec.uobaghdad.edu.iq

Abstract

This paper assesses the impact of changes and fluctuations in bank deposits on the money supply in Iraq. Employing the research constructs an Error Correction Model (ECM) using monthly time series data from 2010 to 2015. The analysis begins with the Phillips-Perron unit root test to ascertain the stationarity of the time series and the Engle and Granger cointegration test to examine the existence of a long-term relationship. Nonparametric regression functions are estimated using two methods: Smoothing Spline and M-smoothing. The results indicate that the M-smoothing approach is the most effective, achieving the shortest adjustment period and the highest adjustment ratio for short-term disturbances, thereby facilitating a return to the long-term equilibrium.

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1. Introduction

Standard studies in economic research aim to develop models and mathematical formulations that express the relationships between various economic variables. This objective is achieved by practically applying economic theories and mathematical economics to real-world scenarios. By leveraging the principles of economic theories and mathematical relationships, researchers can model economic phenomena or construct mathematical models that express these phenomena. This involves formulating problems using equations or inequalities to represent the quantitative relationships among various factors and conditions influencing the issue. These mathematical formulations enable researchers to find solutions using established mathematical methods.

Understanding the historical path of the studied phenomenon and the elements influencing it is crucial in this process. This understanding necessitates the collection of statistical data over time, typically presented in the form of time series. By analyzing this data, researchers can identify patterns and relationships that inform the construction of accurate and predictive economic models.

This paper focuses on employing both descriptive and econometric methods to assess the impact of changes and fluctuations in bank deposits on the money supply in Iraq, using monthly time series data from 2010 to 2015.

One of the modern statistical methods that focus on studying the relationship between variables over the long run, even when these variables deviate from their equilibrium values in the short term, is cointegration analysis. This method addresses situations where differences between variable values allow for the re-stabilization of time series, thereby preserving information about the long-term behavior of these variables.

Granger's contributions have been instrumental in clarifying the concept of cointegration between two or more variables, statistically demonstrating the presence of a long-term equilibrium relationship among them. This approach has become particularly useful in cases where long-term relationships significantly impact the current value of the variable under study. Cointegration analysis thus underscores the importance of considering long-term equilibrium in time series analysis.

The application of cointegration is in line with modern trends in time series analysis, which have played a prominent role in making economic relationships measurable and quantifiable. These advancements have enhanced the ability of researchers to model and predict economic phenomena accurately. By leveraging these methods, this paper aims to assess the impact of changes and fluctuations in bank deposits on the money supply in Iraq, using a robust econometric framework that incorporates cointegration analysis and other advanced statistical techniques.

Most economic data are described as non-stationary time series, which makes regression relationships between their variables susceptible to the problem of spurious regression, leading to inaccurate and unreliable results. To address this issue, cointegration analysis is employed. By focusing on the residuals of the model, cointegration analysis can overcome this problem and establish a long-run equilibrium relationship between two or more variables.

Classical estimation methods sometimes fail to provide satisfactory results for making precise and clear investment decisions or for effective short and long-term planning. Parametric regression models, which assume a linear relationship between variables, do not account for the influence of nonlinear variables, thereby negatively affecting their estimates. Cointegration analysis, on the other hand, offers a robust approach to capturing these complex relationships, ensuring more accurate and reliable modeling of economic data.

This research aims to present and compare statistical methods for detecting the stability of time series and identifying spurious regression, as well as their impact on the relationships between economic variables. The goal is to determine the appropriate mathematical model representing error correction models (ECMs) and to establish their statistical significance. This involves calculating the error correction coefficient, which represents the relationship between the dependent and independent variables, by applying cointegration regression methodology and the ECM.

To obtain accurate estimates, robust nonparametric estimation techniques are employed. These methods are well-suited for data with unknown distributions and have the capability to handle nonlinear models, thereby providing more effective estimates than traditional parametric methods. Specifically, this research applies the Smoothing Spline and M-Smoother methods to achieve these goals.

Numerous studies have explored advanced statistical methods for analyzing economic data. Irizarry (2004) utilized periodic smoothing splines to fit a periodic signal plus noise model to data, assuming underlying circadian patterns. He then established a connection between smoothing splines and REACT estimators.

Nchor and Adamec (2016) investigated the factors influencing real money aggregates in Ghana from 1990 to 2014. Their results indicated that the Gross Domestic Product (GDP) affects the demand for money in the long run, while interest rates influence it in the short run. The error correction term revealed that 18% of deviations in the real demand for money are corrected annually. The CUSUM tests confirmed the stability of the money demand function over the period, and the Chow test showed no structural breaks.

Hmood and Burhan (2018) estimated the transfer function using nonparametric methods, such as Local Linear Regression and Cubic Smoothing Spline, and semiparametric methods represented by a Single Index model. They concluded that the proposed estimator outperformed other estimators.

Adams and AdeyemiIpinyomi (2019) compared three methods; generalized maximum likelihood, generalized cross-validation, and unbiased risk with a proposed smoothing method to estimate the degree of smoothness of Spline Smoothing techniques for time series data, assuming independent error terms. Their goal was to identify the most effective and consistent method for estimating smoothing parameters.

In 2020, Makawi examined the factors affecting Algeria's Gross Domestic Product (GDP) from 1980 to 2017 using simultaneous integration, multiple linear regression, and Granger causality tests. This study included an examination of the stationarity of the series using the Augmented Dickey-Fuller (ADF) test.

2. Cointegration

Cointegration is an econometric method used to determine the long-run equilibrium relationship between variables. This method requires that the variables under consideration are nonstationary in their levels but share the same order of integration, becoming stationary after taking first or second differences. Cointegration is defined as the co-movement between two or more series, where fluctuations in one series are offset by fluctuations in another, maintaining a constant ratio between their values over time.

In quantitative analysis of economic indicators, after confirming the stationarity of individual time series and determining their order of integration, the existence of cointegration between the series can be established. Cointegration indicates a long-term balanced relationship between two or more variables if they exhibit the same trend. This implies that despite short-term deviations, the variables will move together in the long run, reflecting a stable equilibrium relationship.

Cointegration regression analysis is a statistical method focused on examining the long-term relationship between variables, even when these variables deviate from their equilibrium values in the short term. Several tests are available to confirm the presence of unit roots in time series, one of which is the Phillips-Perron test, introduced by Phillips and Perron in 1988. This test corrects for autocorrelation in the residuals of the unit root test equation by applying a nonparametric adjustment to the model's variance, thus accounting for the presence of autocorrelation.

The Phillips-Perron test addresses the issues of residual autocorrelation and non-constant variance of the error term that can arise in the standard Dickey-Fuller test. The test procedure involves four key steps:

1. Estimation of the three basic models for the Augmented Dickey-Fuller (ADF) test using ordinary least squares with calculation of associated statistics.

2. Calculate the associated statistics for each model, including t-statistics for the coefficient of the lagged variable.

3. Compute the short-term variance of the residuals $\sigma^2 = \frac{1}{n}\sum_{t=0}^{n} e_t{}^2$, where e_t represents the residual estimates from the ADF test models, and n is the number of observations..

4. Estimate the long-term correction factor s^2, which accounts for the structure of pre-estimated residual variances, that can be determined based on the structure of pre-estimated residual variances,

$$S_t^2 = \frac{1}{n}\sum_{i=1}^{n} e_t^2 \ + 2\sum_{i=1}^{n}\left(1 - \frac{i}{t-1}\right)\frac{1}{n}\sum_{t=i+1}^{n} e_t\, e_{t-1} \tag{1}$$

This kind of variances requires knowledge of the number of lags estimated by the number of observations (n).

5. Calculate the Phillips-Perron statistics $ppt_{\emptyset}^{*}$; using the following formula:

$$ppt_{\emptyset}^{*} = \sqrt{K} \times \frac{(\emptyset_1 - 1)}{\sigma_{\emptyset 1}} + \frac{n(K-1)\sigma_{\emptyset 1}}{\sqrt{K}} \tag{2}$$

where:

- $K = \frac{\sigma^2}{S_t^2}$ represents the ratio of short-term variance σ^2 to long-term correction factor S_t^2 . In the case where e_t approximates white noise, K equals one.
- $\emptyset_1$ is the estimated coefficient from the ADF test.
- $\sigma_{\emptyset 1}$ denotes the standard error of the coefficient $\emptyset_1$.

After computing $ppt_{\emptyset}^*$, compare it against critical values from the Mackinnon table (1991). If $ppt_{\emptyset}^*$ exceeds these critical values, it indicates the presence of a unit root in the time series, thereby suggesting nonstationary. This method ensures reliable identification of unit roots, crucial for subsequent econometric analysis.

3. Engle and Granger Methodology

According to this methodology, the cointegration test follows the algorithm introduced by Engle and Granger (1987), which involves two stages.

Testing the degree of integration of variables:

The essential requirement for cointegration is that both series must be integrated to the same order. If they are integrated to different orders, they do not exhibit cointegration. Thus, accurately identifying the general trend and the integration order (d) of each variable is crucial for determining cointegration in the series under study.

Estimating the long-term relationship:

To test the null hypothesis that both Y_t and X_t do not have a common level of integration within the Engle-Granger (EG) model framework, a test is conducted assuming the error term (residuals) is integrated at the I(0) level. The steps for conducting the cointegration test are as follows:

1. The long-term relationship between the variables is estimated using the following cointegration formula:

$$Y_t = \alpha + f(X_t) + e_t \tag{3}$$

After estimation, the residuals are obtained using the following formula:

$$\hat{e}_t = Y_t - \hat{\alpha} - \hat{f}(X_t) \tag{4}$$

To confirm the presence of a cointegration relationship, it is essential that the estimated residuals $\hat{e}_t$ are stationary. This stationarity is typically verified using tests such as the Phillips-Perron or Dickey-Fuller tests.

2. The stationarity of the residuals is assessed by estimating the following formula:

$$\hat{e}_t = Y_t - (\hat{\alpha} + \hat{f}(X_t)) \tag{5}$$

The calculated value of τ_α is compared with critical values from tables developed by Engle and Granger. $\tau_\alpha = \frac{\hat{\alpha}}{S_{\hat{\alpha}}}$

Mackinnon (1991) generated tables based on the number of observations and the number of independent variables involved in the stationary relationship. If the computed τ_α exceeds the critical value, the null hypothesis is rejected, indicating stationary residuals and confirming cointegration in the series data. This allows for the estimation of the Error Correction Model (ECM).

4. Error Correction Model (ECM)

Economic variables characterized by long-term cointegration tend towards stability or equilibrium. However, occasional temporary shocks may cause these variables to deviate temporarily from their equilibrium path. Therefore, the Error Correction Model (ECM) is employed to capture and model the dynamics between the long-term and short-term behaviors of economic relationships.

The Error Correction Model (ECM) embodies an adjustment mechanism that integrates short-term fluctuations into the long-term relationship. The term "Error Correction Model" denotes its capacity to rectify short-term deviations from the long-term equilibrium. By employing the ECM, we can scrutinize and understand the short-term dynamics of variables, aiming for long-term equilibrium. According to Engle and Granger (1987), estimating the ECM involves incorporating lagged long-term residuals of the relationship as independent variables.

Based on Granger's theory, the dynamic model of integrated series can be transformed into an Error Correction Model (ECM), which is considered superior to partial adjustment models for studying the response of the dependent variable. This is because the ECM incorporates both short and long-term information, addressing short-term disequilibrium and adjusting towards long-term equilibrium. Consequently, it provides consistent estimates for both short-term dynamics and long-term trends.

To estimate the ECM according to Engle and Granger, the following steps are required:

1. Verify the stationarity of the model variables and determine the order of integration of each variable separately by testing for unit roots.
2. Ensure a cointegrated relationship between the model variables through cointegration testing.

The relationship between the response variable and the explanatory variable can be formulated as follows:

$$Y_t = \alpha + BX_t + e_t \tag{6}$$

Where $\mathrm{Y_t}$ and $\mathrm{X_t}$ are first-order integrated time series I(1). So to clarify the error correction model the following steps are followed:

Estimate the long-term relationship between Y_t and X_t.

$$\hat{Y}_t = \hat{\alpha} + \hat{\beta} X_t \tag{7}$$

Estimate the dynamic relationship for both the short and long term as follows:

$$\Delta \mathrm{Y_t} = \alpha_1 \Delta \mathrm{X_t} - \alpha_2 \mathrm{e_{t-1}} + \mathrm{e_t} \tag{8}$$

$$\Delta\hat{Y}_t = \hat{\alpha}_1 \Delta X_t - \hat{\alpha}_2 (Y_{t-1} - \hat{\alpha} - \hat{\beta} X_{t-1}) + \hat{e}_t \tag{9}$$

Where:

Δ: represents the first difference.

$\hat{\alpha}_1$: represents the short-term coefficient.

$\hat{\beta}$: represents the long-term response of Y_t to X_t.

α_2: represents the error correction term (ECT) coefficient, which indicates the speed of adjustment towards long-term equilibrium.

The above equations illustrate that the change in $\mathrm{Y_t}$ depends on the change in $\mathrm{X_t}$as well as the lagged error correction term. The model measures how $\mathrm{Y_t}$ adjusts to return to equilibrium, represented by the error correction term α_2.

When estimating this equation, lagged values of residuals are incorporated as explanatory variables to ensure that the random error does not exhibit autocorrelation, particularly when high lag values are included. The model is then adjusted as follows:

$$\Delta Y_t = \sum_{i=1}^{p} \rho_i \Delta Y_{t-i} + \sum_{i=0}^{q} \alpha_i \Delta X_{t-i} - \alpha_2 (Y_{t-1} - \alpha - \beta X_{t-1}) + e_t \tag{10}$$

$$\Delta Y_t = \alpha_0 + \sum_{i=1}^{p} \rho_i \Delta Y_{t-i} + \sum_{i=0}^{q} \alpha_i \Delta X_{t-i} - \alpha_2 ECT_{t-1} + e_t \tag{11}$$

5. Cubic Spline Smoother

Smoothing Spline is a statistical method used to estimate the nonparametric regression function, allowing the establishment of a nonlinear relationship between pairs of random variables and to discover patterns or structures in the data without requiring a parametric model. Spline method, a widely utilized smoothing technique, relies on the residual sum of squares (RSS) to measure the goodness of fit of the function $f(.)$ to the data. The RSS is defined as follows:

$$RSS = \sum_{t=1}^{n} \{Y_t - f(X_t)\}^2 \tag{12}$$

The necessary condition for the function $f(X_t)$ is that it must be twice differentiable, allowing for the computation of its second derivative. In Spline smoothing, the number of knots is equal to the number of observations in the time series studied, i.e., (knots = n). Non-smoothed penalty solution methods have been proposed to calculate the non-smoothed part.

If we have n observations of the time series values $X_1, X_2, \dots, X_n$ represented over the time interval [a,b], then the function f is defined as a Cubic Spline if the following conditions are met:

1. The function f is a Cubic Polynomial Spline with multiple boundaries in the intervals $(a, X_1), (X_1, X_2), \dots, (X_n, b)$.
2. The piecewise polynomial with multiple boundaries is appropriate at point X_t for the first and second derivatives of the function f and is continuous at the points X_t, i.e. f is continuous in the interval [a,b].

The concept behind spline smoothing is to place a knot at each data point. Parameter estimation is achieved by minimizing the sum of squares in addition to the penalty term. Cubic splines are represented as a continuous curve, and the goal of this method is to find a smoothing estimator that minimizes the sum of squared penalized residuals, combined with the roughness penalty.

$$\sum_{t=1}^{n}[Y_t - f(X_t)]^2 + \lambda \int [f''(X)]^2 dx \tag{13}$$

We can use the Reinsch algorithm to calculate the estimator (Green and Silverman [1994]). The selection of the penalty parameter λ is crucial, as it balances the goodness of fit and the roughness penalty. One technique for estimating this parameter is Generalized Cross Validation (GCV). This approach can be summarized by the following formula:

$$GCV(\lambda) = \frac{1\sum_{t=1}^{n}\{Y_t - \hat{f}_\lambda(X_t)\}^2}{n\{1-\frac{1}{n}Trace(S_\lambda)\}^2} = \frac{\frac{1}{n}\|(1-S_\lambda)Y\|^2}{\left[\frac{1}{n}Trace(1-S_\lambda)\right]^2} \tag{14}$$

Given that:
n: the number of pairs of observations (X_t, Y_t).
λ: the penalty parameter.
S_λ: the hat matrix, defined as $(X'WX)^{-1}X'W$.
Trace: the trace of the matrix.

6. M-Smoother

The local robust smoothing technique, based on local estimates, is denoted as the M-Smoother.

$$\hat{f}(x) = n^{-1}\sum_{t=1}^{n} W_{nt}(x) Y_t \tag{15}$$

This smoother can be considered a solution to the challenges faced in local least squares methodology. The core concept behind this smoother is to reduce the influence of outliers or contaminated data by using the following loss function:

$$\rho(u) = \begin{cases} (1/2)u^2 & if\ \lfloor u \rfloor \le c \\ c\lfloor u \rfloor - (1/2)c^2 & if\ \lfloor u \rfloor > c \end{cases} \tag{16}$$

The constant (c) determines the robustness of the estimator. A larger (c) yields the classical quadratic loss function, while smaller values, such as one or two, increase robustness against the standard deviation of observation errors. The formulation of the M-estimator using Spline smoothing, as defined by Cox (1983), is:

$$argmin_{(f)}\{n^{-1}\sum_{t=1}^{n}\rho\big(Y_t - f(X_t)\big) + \lambda \int [f''(x)]^2\, dx\} \tag{17}$$

Here, ρ represents a loss function with tails lighter than the quadratic function. Assuming the conditional distribution of $F(.|x)$ is symmetric allows for the estimation of the conditional mean curve. The definition of the local M smoother $\hat{f}_h^M(x)$ is as follows:

$$argmin_\theta\ \{n^{-1}\sum_{t=1}^{n} W_{ht}(x)\rho(Y_t - \theta)\} \tag{18}$$

Where $\{W_{ht}(x)\}_{t=1}^{n}$represents the weight sequence. If $\rho(Y_t - \theta)$ is differentiated with respect to θ, the formulation becomes:

$$argmin_{\theta}\,\{n^{-1}\sum_{t=1}^{n} W_{ht}(x)\psi(Y_t-\theta)\}\,,\psi=\rho'. \tag{19}$$

7. Application

To assess how fluctuations in bank deposits affect the money supply, we analyzed data from the Central Bank of Iraq for the period 2010 to 2015. MATLAB 2018 and EViews 12 were used for data analysis. The study aimed to investigate the relationship between these variables using the Engle-Granger methodology. An essential step in this approach involves confirming the integration level of the time series, which was validated using Unit Roots tests, specifically emphasizing the Phillips-Perron test.

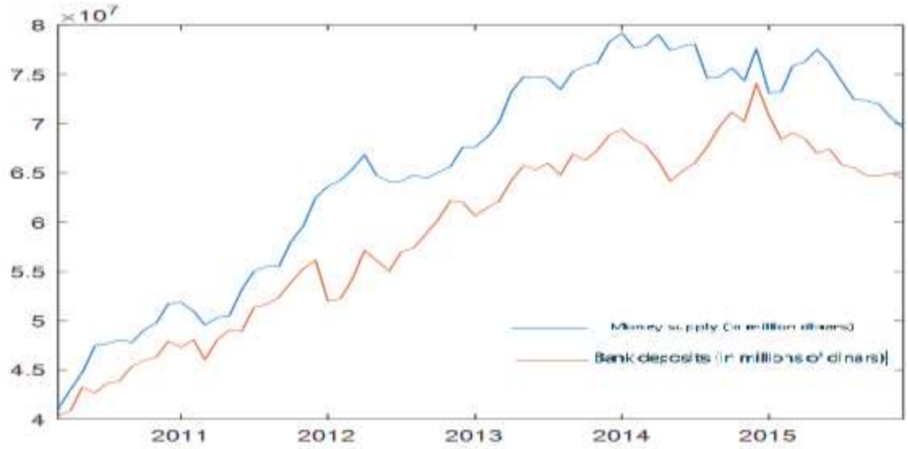

Figure 1: The time series of Deposit Banks and Money Supply (in million dinars)

Through plotting the time series of the study variables, it becomes clear that they display non-stationarity at level zero, i.e., I(0). To verify this, Unit Roots tests were performed at both I(0) and first differences I(1) levels, employing the Phillips-Perron test. Table (1) displays the results of this test for the Money Supply at the I(0) and I(1) levels, respectively.

Table 1: Philips-Perron Test Results for Unit Root for the Money Supply.

	Without Intercept and trend		Intercept		Intercept and Trend	
Money Supply	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
Statistic	1.491313	-7.049863	-2.781339	-7.361504	-0.161926	-8.162404
P-Value	0.9654	0.0000	0.0662	0.0000	0.9927	0.0000
Decision	Non-Stationary	Stationary	Non-Stationary	Stationary	Non-Stationary	Stationary

Table 1 shows the Money Supply variable's time series was non-stationary at level zero, I(0), suggesting the presence of a unit root in this variable. After applying the first difference, I(1), the test shows that the Money Supply variable becomes stationary. Similarly, the series of bank deposits is examined in Table 2, presenting results for tests at I(0) and I(1) levels.

Table 2: Philips-Perron Test Results for Unit Root for the Bank Deposits Variable.

	Without Intercept and trend		Intercept		Intercept and Trend	
Bank Deposits	**I(0)**	**I(1)**	**I(0)**	**I(1)**	**I(0)**	**I(1)**
Statistic	1.589896	-7.971769	-2.234954	-8.344357	-0.726531	-9.014974
P-Value	0.9717	0.0000	0.1961	0.0000	0.9668	0.0000
Decision	Non-Stationary	Stationary	Non-Stationary	Stationary	Non-Stationary	Stationary

Form reviewing the results from the aforementioned tables, it becomes apparent that the variables are integrated at the first difference level, I(1), enabling the application of the Engle-Granger cointegration test methodology. After conducting the stationarity analysis of the variables, it is observed that all variables are nonstationary at level I(0), indicating the presence of a Unit Root with computed values significantly below the critical Mackinnon values. However, after first differencing the time series of the variables, they become stationary, indicating first-order integration, I(1).

The Engle-Granger cointegration test requires the time series to be non-stationary at level I(0) but integrated at the same order. Once this condition is confirmed (i.e., the series are stationary at the first difference I(1) level), the Engle-Granger cointegration test is applied between the series to determine the existence of a long-term equilibrium relationship between the money supply and bank deposits. This relationship is estimated using Ordinary Least Squares (OLS) regression. However, in our study, we will employ two non-parametric estimation methods.

Table 3: The results of the Phillips-Perron test for residuals at level I(0).

Method	M-smoothing	Cubic Spline
Phillips-Perron	-4.969021	-3.526886
1% level	-2.598907	-2.598907
5% level	-1.945596	-1.945596
10% level	-1.613719	-1.613719
P.value.	0.000	0.0006

From Table 3, it is evident that the t-test statistic values for both methods exceed the critical values at all levels. Therefore, the null hypothesis of the presence of a unit root in the residual series is rejected, this implies that the error series has not unit root, indicating stationarity at level I(0), or in other words, the variables are integrated at the first order I(1). This signifies the presence of cointegration among the time series variables, indicating a long-term relationship between them.

Consequently, an Error Correction Model (ECM) can be estimated to verify their joint integration, revealing a long-term equilibrium relationship between the money supply and bank deposits (Engel and Granger, 1987).

The Error Correction Model (ECM) allows for testing and estimating this relationship over the long term, as well as identifying its direction in both the short and long terms. The Error Correction Term (ECT), or Speed of Adjustment, indicates how the dependent variable changes in response to deviations of the independent variable from its long-term equilibrium by one unit in the short term. This coefficient typically is negative, indicating the speed at which the short-term relationship adjusts towards the long-term equilibrium. The coefficients themselves reveal the direction of the relationship in the short term.

Table 4: Estimation of the Error Correction Model (ECM)

	Variable	Coefficient	Std. Error	t-Statistic	P-Value
Cubic Spline Smoother	**C**	251679.0	153873.2	1.635626	0.1067
	D(X)	0.500249	0.102325	4.888838	0.0000
	U(t-1)	-0.240303	0.072705	-3.305197	0.0015
	R-Squared	0.330980	**Mean Dependent Variable**		414170.4
	Adjusted R-	0.310707	**Sum Squared Residual**		1.02E+14
	F-Statistic	16.32590	**Akaike Info. Criterion**		30.94782
	P-Value	0.000002	**Durbin-Watson (D.W.)**		1.394426
M Smoothing	**C**	248923.1	161563.7	1.540712	0.1282
	D(X)	0.507607	0.108408	4.682370	0.0000
	U(t-1)	**-0.267463**	0.137685	1.942565	**0.0563**
	R-Squared	0.262416	**Mean Dependent Variable**		414170.4
	Adjusted R-	0.240065	**Sum Squared Residual**		1.13E+14
	F-Statistic	11.74064	**Akaike Info. Criterion**		31.04539
	P-Value	0.000043	**Durbin-Watson (D.W.)**		1.675044

Based on the results from Table 4, the Error Correction Term (ECT) coefficient using the Cubic Spline Smoother is statistically significant with a p-value of 0.0015 and is negative at approximately -0.240303. This suggests that adjustments from short-term disequilibrium to long-term equilibrium occur at a rate of about 24% per month. In practical terms, it would take approximately $\frac{1}{-0.240303} = -4.16$ months for the money supply to return to its long-term equilibrium level after a shock in bank deposits, assuming other factors remain constant.

Similarly, with the M-smoother, the ECT coefficient is negative and statistically significant with a p-value of 0.0563, approximately -0.267463. This indicates an adjustment rate of around 27% per month, translating to an estimated correction time of about $\frac{1}{-0.267463} = -3.7$ months for the money supply to revert to its long-term equilibrium level following a bank deposits shock.

Examining the coefficients of both models reveals a statistically significant positive effect of bank deposits on the money supply in the short term. Specifically, an increase of one unit in bank deposits leads to an increase in the money supply by approximately 0.500249 and 0.507607 units for the Cubic Spline and M smoothers, respectively.

The coefficient of determination (R-squared) for the models is 0.330980 and 0.262416, indicating that approximately 33% and 26% of the variations in the money supply are explained by bank deposits, while the remainder is attributed to errors or other unaccounted-for factors. Furthermore, the Durbin-Watson statistics (DW) are 1.394426 and 1.675044, respectively, suggesting no Autocorrelation among the residuals of the models.

8. Conclusions

1. The analysis indicated that the variables in the model (Money Supply and Bank Deposits), were non-stationary at their levels (I(0)), but achieved stationarity after first differencing, indicating they are integrated of order one (I(1)).
2. The Engle-Granger cointegration test confirmed a long-term equilibrium relationship between Money Supply and Bank Deposits, suggesting that these variables move together in the long run.
3. Both estimation methods revealed a statistically significant positive relationship between Money Supply and Bank Deposits.
4. The ECM estimation results using the Engle-Granger methodology showed that Bank Deposits explain approximately 33% of the variations in Money Supply when using the Cubic Spline Smoother and 26% when using the M-Smoother.

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استعمال أنموذج تصحيح الخطأ لاستكشاف تأثير التقلبات في الودائع البنكية على عرض النقد

ميسون عبد حسين	ا.د. مناف يوسف حمود
maysoon.Abdulhusseinl1201a@coadec.uobaghdad.edu.iq	munaf.yousif@coadec.uobaghdad.edu.iq
قسم الاحصاء، كلية الادارة والاقتصاد، جامعة بغداد، بغداد، العراق	

المستخلص

في هذا البحث تم دراسة تأثير التغيرات والتقلبات في الودائع المصرفية على عرض النقود في العراق. اذ تم بناء أنموذج تصحيح الخطأ (ECM) بالاعتماد على بيانات سلسلة زمنية شهرية للمدة من عام 2010 ولغاية عام 2015.

تحليل السلسلة الزمنية تركز على اختبار جذور الوحدة باستعمال اختبار فيليبس- بيرون وذلك لغرض التحقق من استقرار السلسلة الزمنية، كذلك اختبار التكامل المشترك لإنجل وجرانجر لفحص وجود علاقة طويلة الأجل. ومن ثم تم تقدير دالة الانحدار اللامعلميه باستعمال طريقتين هما:تمهيد الشريحة وكذلك التمهيد باستعمال طريقة M الحصينة. اثبتت النتائج تفوق طريقة M الحصينة ، اذ حققت أقصر فترة تعديل وأعلى نسبة تعديل للاضطرابات قصيرة الأجل، مما يجعل العودة إلى التوازن طويل الأجل بشكل اسرع.

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للمراسلة:

مناف يوسف حمود

munaf.yousif@coadec.uobaghdad.edu.iq

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